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On-line Image Search Re-ranking based on Interaction

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Abstract- The methods available for image search are based on the text provided in the search. but such kind of image search re-ranking suffer from unreliability because the resulting images contain more irrelevant images. Hence the re-ranking concept arises to re-rank the retrieved images based on the text surrounding the image and metadata and visual feature.

In this paper, we propose an **"On-line image search re-ranking based on Interaction"** Which follows supervised learning. Here the top-ranked images are considered as (noisy) training data & an SVM visual classifier is learned to improve the ranking further. Given the keyword as input to the proposed model the output will contain a set of images which will be more near to user search requirement.

Keywords: reranking ,meta reranker, Prototype Based Reranking, image search, noise ,SVM, supervised learning

I. INTRODUCTION

The search engines search images mostly by using the text associated with the images like title title of the images. This is often good to search relevant images but the problem is that precision of search result is less .Methods like Clustering[7], topic modeling[6],[2], Support Vector machine (SVM)[8], graph learning[9],[10] have been investigated for visual reranking All these require prior assumption regarding the relevance of images in initial text based search result . Also Top N search results can also contain irrelevant images which introduce noise. So here we propose solution named as **"On-line image search re-ranking based on Interaction"** a prototype based method to learn reranking function from human labeled samples. Based on images obtained in initial search result, visual prototype will be generated .Each prototype is used to construct a meta reranker to produce a reranking score for any other image from initial set. Finally all scores from all meta rerankers are aggregated. For visual reranking we use SVM algorithm.Support Vector Machine (SVM) adapts widely used SVM classifier to handle a ranking problem . SVM have recently gained prominence in the field of machine learning and pattern classification. Classification is achieved by realizing a linear or non-linear separation surface in the input space.

II. LITERATURE SURVEY

Mario Fritz and Bernt Schiele[2]. presented a novel method for the discovery and detection of visual object categories based on decompositions using topic models. The approach is capable of learning a compact and low dimensional representation for multiple visual categories from multiple view points without labeling of the training instances. The learnt object components range from local structures over line segments to global silhouette-like descriptions. This representation can be used to discover object categories in a totally unsupervised fashion. Furthermore it employ the representation as the basis for building a supervised multi-category detection system making efficient use of training examples and outperforming pure features-based representations.

***Winston H. Hsu,Lyndon S. Kennedy,Shih-Fu Chang[3*],** have their work in video serach reranking. Multimedia search over distributed sources often result in recurrent images or videos which are manifested beyond the textual modality. To exploit such contextual patterns and keep the simplicity of the keyword-based search, they proposed novel reranking methods to leverage the recurrent patterns to improve the initial text search results. The approach, context reranking, is formulated as a random walk problem along the context graph, where video stories are nodes and the edges between them are weighted by multimodal con- textual similarities.
When evaluated on TRECVID 2005 video benchmark, the pro-posed approach improve retrieval on the average up to 32% relative to the baseline text search method in terms of story-level Mean Average Precision. In the people-related queries, which usually have recurrent coverage across news sources, we can have up to 40% relative improvement. Most of all, the proposed method does not require any additional input from users (e.g., example images), or complex search models for special queries (e.g., named person search).

Li-Jia Li · Li Fei-Fei [4] proposed automatic online picture collection via incremental model learning. The explosion of the Internet provides us with a tremendous resource of images shared online. It also confront vision researchers the problem of finding effective methods to navigate the vast amount of visual information. Semantic image understanding plays a vital role towards solving this problem. One important task in image understanding is object recognition, in particular, generic object categorization. Critical to this problem are the issues of learning and dataset. Abundant data helps to train a robust recognition system, while a good object classifier can help to collect a large amount of images. This paper presents a novel object recognition algorithm that performs automatic dataset collecting and incremental model learning simultaneously. The goal of this work is to use the tremendous resources of the web to learn robust object category models for detecting and searching for objects in real-world cluttered scenes.

LinjunYang,AlanHanjalic[5] proposed supervised reranking for web image search**.**
Visual search reranking that aims to improve the text-based image search with the help from visual content analysis has rapidly grown into a hot research topic. The interestingness of the topic stems mainly from the fact that the search reranking is an unsupervised process and therefore has the potential to scale better than its main alternative, namely the search based on offline-learned semantic concepts. However, the unsupervised nature of the reranking paradigm also makes it suffer from problems, the main of which can be identified as the difficulty to optimally determine the role of visual modality over different application scenarios.

***R. Fergus, L. Fei-Fei, P. Perona, and A. Zisserman* [6]**, have proposed the idea of training using just the objects name by bootstrapping with an image search engine. The training sets are extremely noisy yet, for the most part, the results are competitive (or close to) existing methods requiring hand gathered collections of images.

***W. H. Hsu, L. S. Kennedy, and S.-F. Chang*[7]** have proposed a novel and generic video/image reranking algo-rithm, IB reranking, which reorders results from text-onlysearches by discovering the salient visual patterns of rele-vant and irrelevant shots from the approximate relevance provided by text results. The IB reranking method, based on a rigorous Information Bottleneck (IB) principle, finds the optimal clustering of images that preserves the maxi- mal mutual information between the search relevance and the high-dimensional low-level visual features of the images in the text search results.

R. Yan, A. G. Hauptmann, and R. Jin, [8] present an algorithm for video retrieval that fuses the decisions of multiple retrieval agents in both text and image modalities. While the normalization and combination of evidence is novel, they emphasizes the successful use of negative pseudo-relevance feedback to improve image retrieval performance.

Y. Jing and S. Baluja, [9] present the image-ranking problem into the task of identifying "authority" nodes on an inferred visual similarity graph and propose VisualRank to analyze the visual link structures among images. The images found to be "authorities" are chosen as those that answer the image-queries well. To understand the performance of such an approach in a real system, they conducted a series of large-scale experiments based on the task of retrieving images for 2,000 of the most popular products queries. Their experimental results show significant improvement, in terms of user satisfaction and relevancy, in comparison to the most recent Google Image Search results. Maintaining modest computational cost is vital to ensuring that this procedure can be used in practice; they describe the techniques required to make this system practical for large-scale deployment in commercial search engines

X. Tian, L. Yang, J. Wang, Y. Yang, X. Wu, and X.-S. Hua[10] They formulates the image reranking problem in the Bayesian framework,i.e.maximizing the ranking score consistency among visually similar video shots while mini-mizing the ranking distance, which represents the disagree-ment between the objective ranking list and the initial text-based. Different from existing point-wise ranking distance measures, which compute the distance in terms of the indi-vidual scores, two new methods are proposed by them to measure the ranking distance based on the disagreement in terms of pair-wise orders. Specifically,hinge distance pe-nalizes the pairs with revers ed order according to the de-gree of the reverse, while preference strength distance further considers the preference degree.

By incorporating the pro-posed distances into the optimization objective, two rerank-ing methods are developed which are solved using quadratic programming and matrix computation respectively. Evalu- ation on TRECVID video search benchmark shows that the performance improvement up to 21% on TRECVID 2006 and 61.11% on TRECVID 2007 are achieved relative to text search baseline

III. PROPOSED SYSTEM

FRAMEWORK AND DESIGN

A. Problem Definition :Image Reranking

Firstly, Retrieve a large number of images for a specified object class from browser.Now assuming we have these N images ,retrieved from initial text-based search results (as in fig 1).Then, the reranking process is used to improve the search accuracy by reordering the images based on information extracted from the initial text based search results , the auxiliary knowledge and the example image (prototype). The auxiliary knowledge can be the extracted visual features from each image.

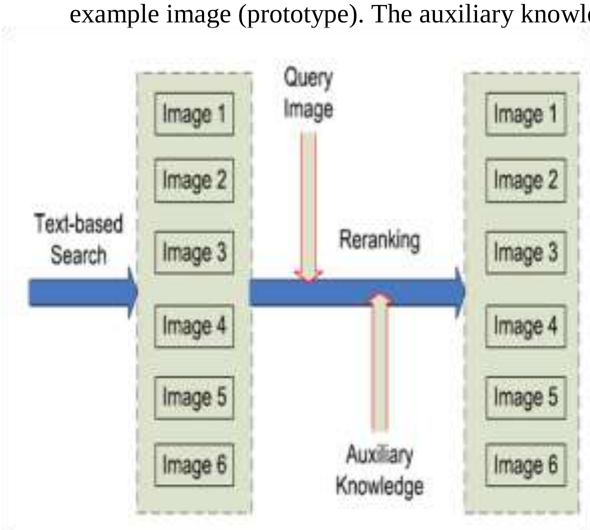

Fig 1 Illustration of reranking problem

In this paper we use a prototype based reranking freamework from [1], which constructs meta rerankers corresponding to visual prototypes representing the textual query and learns the weights of a linear reranking model , is used to combine the results of individual meta rerankers and produce the reranking score of a given image taken from initial text based search result.

B. Block Diagram

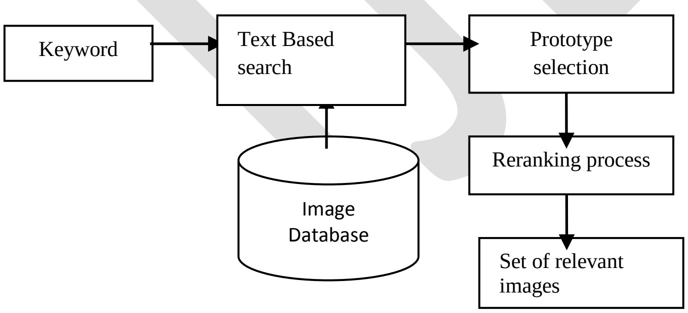

Fig 2 Proposed on-line image reranking system framework

C. Working:

1. Candidate images are obtained by a text based web search querying on object identifier e.g. keyword “cat”.

2. Then noise (irrelevant images) are to be removed and reranked remaining set of images. For ranking surrounding text as well as visual features are used.
3. To the top ranked images, visual classifier is learned and visual prototype is generated, that visually represent a query.
4. Final output is reranked images.

In short the process can be redefines sequentially in following algorithm.

Algorithm:

1**:** start
2: User requests an image to Search Engine like Google.
3: Search Engine collects images and stores it in the database.
4: Then, Filter images by removing symbols and drawings from the collected images.
5: Rerank filtered images using metadata such as text, color.
6: Rerank images using SVM algorithm.
7: Get the SVM reranking result which is more relevant to the image requested by user.
8**:** Render the relevant images to the user.
9: Stop

IV. CONCLUSION

Here the proposed a prototype-based reranking framework, which constructs meta rerankers corresponding to visual prototypes representing the textual query and learns the weights of a linear reranking model to combine the results of individual meta rerankers and produce the reranking score of a given image taken from the initial text-based search result. The induced reranking model is learned in a query-independent way requiring only a limited labeling effort and being able to scale up to a broad range of queries. The experimental results on the Web Queries dataset demonstrate that the proposed method outperforms all the existing supervised and unsupervised reranking methods. It improves the performance over the text-based search result by combining prototypes and textual ranking features.

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